

The Use of Principal Components Analysis (PCA) in Processing AIRS Data

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Applications of Eigenvectors to AIRS Data

- NESDIS is processing and distributing AIRS data and products in near-real time to NWP centers.
- Data size is very large compared with current sounders (1 orbit ~ 2GB vs. 8 MB)
- Information is not independent. Eigenvectors provide an effective way to extract independent pieces of information.
- Eigenvector expansion coefficients (principal component scores) can be provided instead of the individual channels.
- Individual channels can be reconstructed with minimal signal loss.



NWP Users

- NCEP
- ECMWF
- Met. Office
- Meteo-France
- Goddard DAO
- Meteor. Service of Canada
- Bureau of Meteorology Research Centre (Australia)
- FNMOC

Principal Component Analysis

- Principal component analysis (PCA) is often used to reduce data vectors with many components to a different set of data vectors with much fewer components that still retains most of the variability and information of the original data
- $\mathbf{R} = r_1 \cdot \mathbf{i}_1 + r_2 \cdot \mathbf{i}_2 + r_3 \cdot \mathbf{i}_3 + \dots + r_n \cdot \mathbf{i}_n$ where $\mathbf{i}_1 = (1,0,0,0,0,\dots,0_n)$; $\mathbf{i}_2 = (0,1,0,0,0,\dots,0_n)$
- Data are rotated onto a new set of axes, such that the first few axes have the most explained variance.
- $\mathbf{R} = p_1.\mathbf{E}_1 + p_2.\mathbf{E}_2 + p_3.\mathbf{E}_3 + \dots + p_n.\mathbf{E}_n$ where \mathbf{E} are eigenvectors and $p_1 = \mathbf{R} \mathbf{E}_1$
- So instead of **R** vectors of length n, we can have a truncated **P** vectors of length m, where m << n



Eigenvectors are used for

Data compression

- Quality control
- Retrievals of geophysical parameters
 - » Atmospheric temperature, moisture and ozone
 - » Surface temperature and emissivity



Generating AIRS eigenvectors

- Each AIRS data vector has 1524 radiance values (Efforts are being made to expand it to over 2000).
- The radiances are normalized by expected instrumental noise (signal to noise)
- Compute the covariance matrix S
- Compute the eigenvectors E and eigenvalues Λ $S = E \Lambda E^T$
- E = matrix of orthonormal eigenvectors (1524x1524) $\Lambda = vector$ of eigenvalues (explained variance)

Applying AIRS eigenvectors

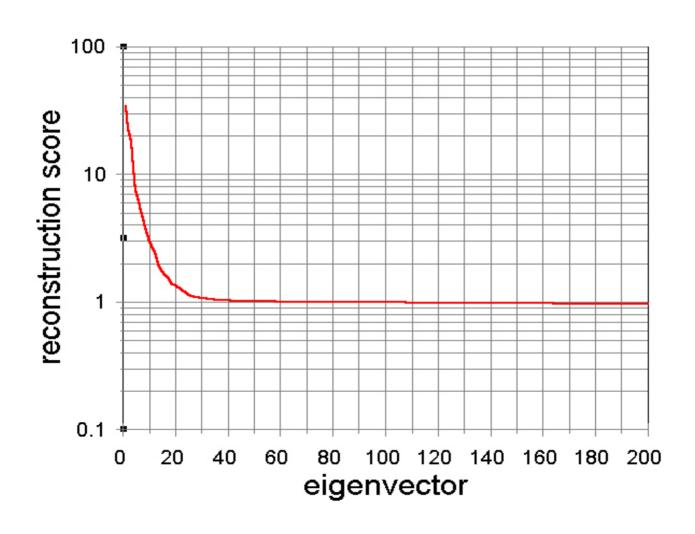
- On independent data compute principal component scores.
- $P = E^T R$; elements of $R = (r_i r_i)/n_i$
- Invert equation and compute reconstructed radiances R*.
- \bullet R* = EP
- Reconstructed radiances are used for quality control.
- Reconstruction score = $[1/N \ 3(R*_i R_i)^2]^{1/2}$ i = 1N channels



AIRS applications

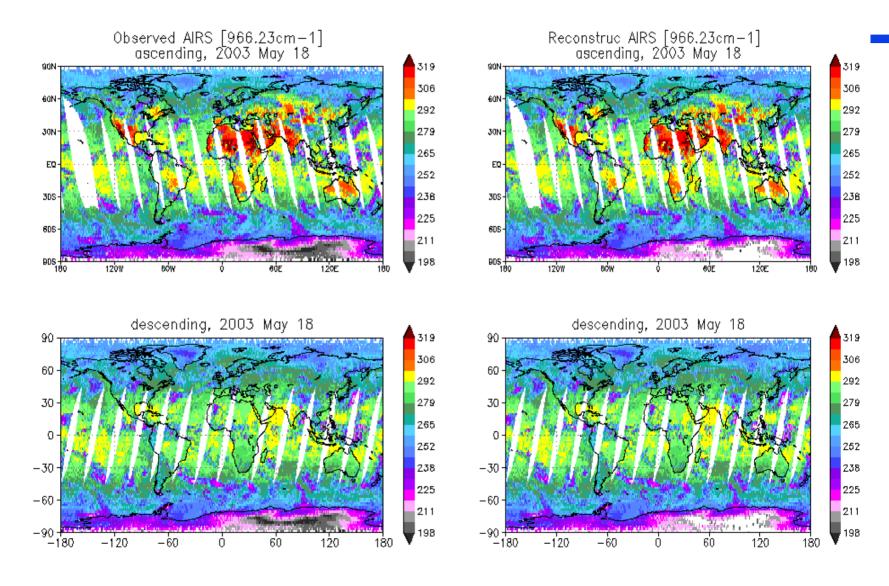
- AIRS is currently being processed and distributed in near-real time.
- Each day a spatial subset of AIRS data is produced (200 mbytes vs 30 GB full data)
- Eigenvectors are generated daily.
- A static set of eigenvectors is used, but the ensemble is occasionally updated with new structures.
- When the ensemble is updated a new set of eigenvectors is also updated.
- Occasional bad channels can be synthesized from neighboring/most correlated channels.

•Reconstruction score = $[1/N \sum (R_i^* - R_i)^2]_{i=1...N}^{1/2}$ channels

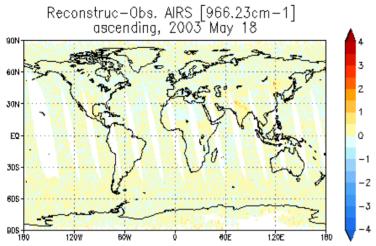




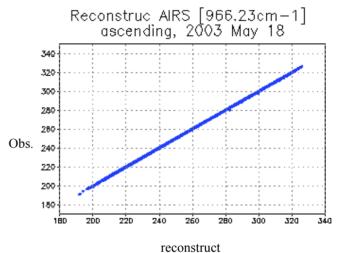
Compare the observed and reconstructed – a window channel



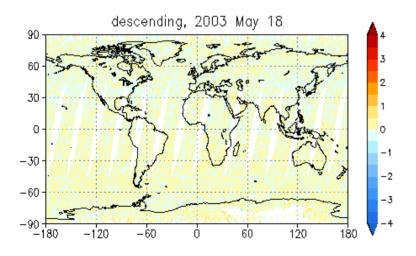


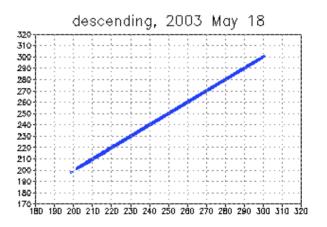






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GrADS: COLA/IGES 2003-05-19-16:48

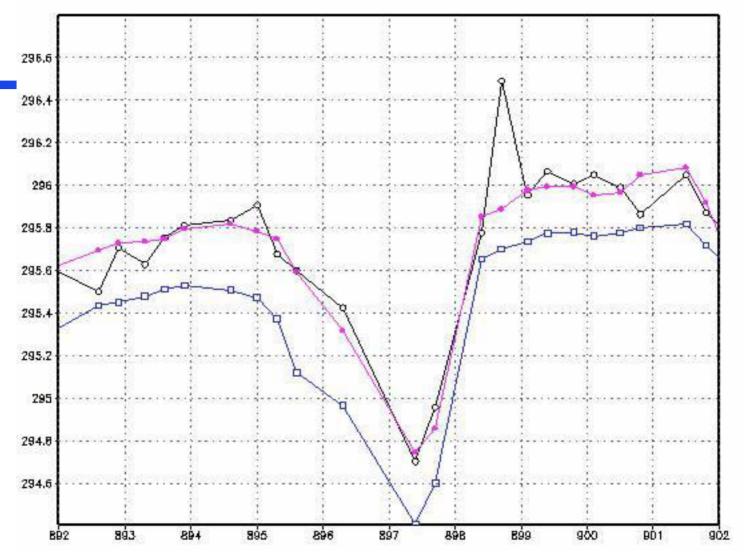


Noise filter

 Truncating eigenvectors also results in noise filtering.

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Spectrum from 892 to 902 wavenumber



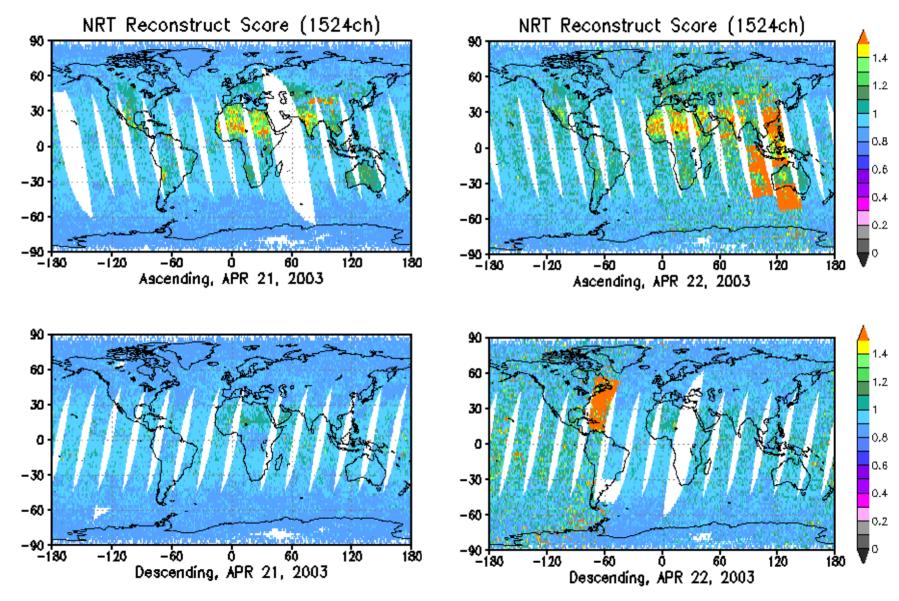
Purple is reconstructed, black is original, blue is calculated from model



Monitoring Eigenvectors

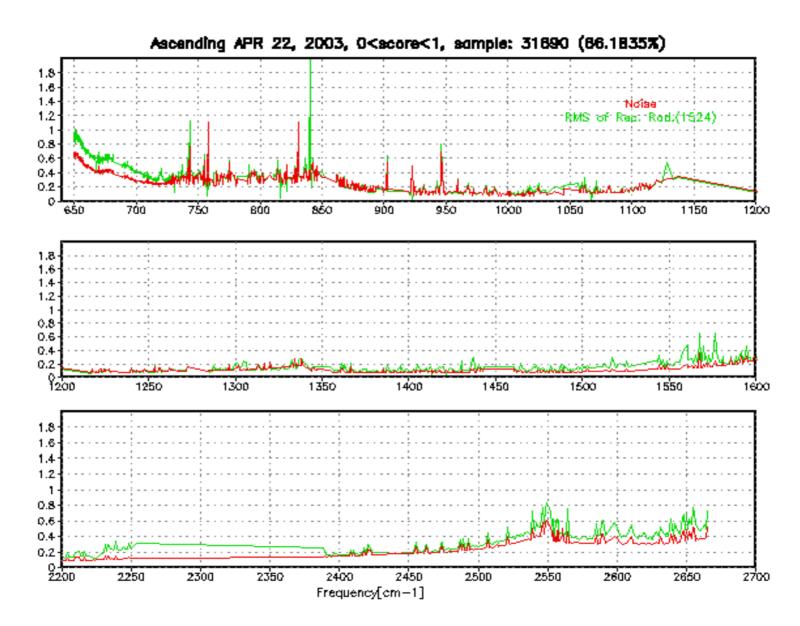
- Monitoring eigenvectors is critical
- Bad channel can be found out by monitoring the reconstruction scores and the difference between the reconstructed and the observed radiances.







AIRS NEDT vs. RMS of Reconstruct Radiance





Indx

frea.

Nedt aveob/avere s<1 asc

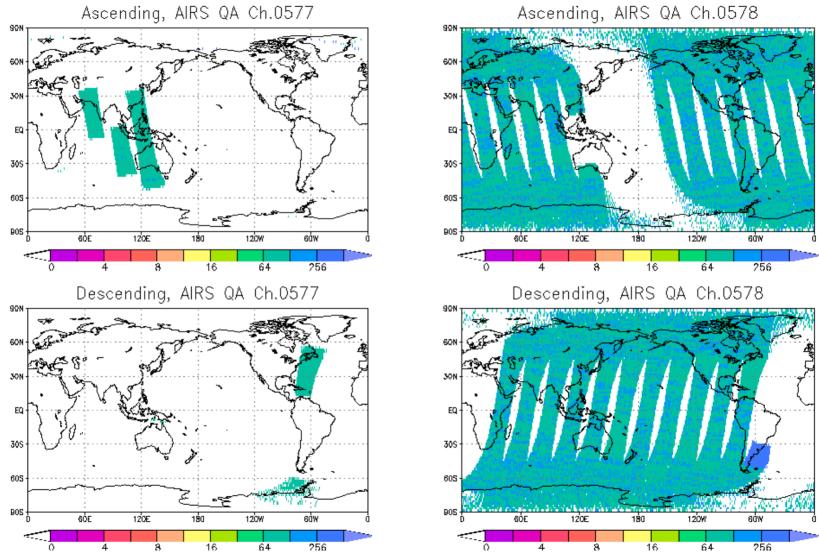
277.15/ 832.810 0.356 0.336 0.336 0.311 0.323 0.350 0.342 0.425 418 0.447 277.19 277.15/ 419 833.201 0.285 0.300 0.300 0.314 0.318 0.375 0.371 0.385 0.398 277.18 277.16/ 833.986 0.349 0.330 0.328 0.298 0.321 0.333 0.433 420 0.311 0.414 277.20 276.72/ 835.166 0.314 0.318 0.321 0.294 0.325 0.507 421 0.309 0.356 0.508 276.75 276.26/ 0.376 0.382 0.396 0.396 422 835.560 0.338 0.4870.508 0.5990.616 276.32 277.13/ 0.788 836.743 0.469 0.585 0.580 0.658 0.628 0.814 0.796 0.743 423 277.15 277.05/ 0.277 0.278 0.278 837.930 0.281 0.255 0.262 0.2810.403 0.428 424 277.09 276.84/ 425 839.121 0.437 0.397 0.405 0.391 0.426 0.441 0.422 0.465 0.455 276.86 271.72/ 426 839.916 0.296 0.344 0.315 2.346 0.608 9.860 4.562 15.296 5.237 272.47 275.40/ 2.204 2.311 427 840.314 0.305 5.578 6.470 10.692 14.757 22.821 24.518 274.21 276.33/ 840.712 0.393 0.379 0.379 0.351 0.375 0.393 0.440 0.605 428 0.643 276.37 276.76/ 429 841.111 0.482 0.1950.198 0.226 0.212 0.325 0.262 0.428 0.435 276.83 276.84/ 842.710 0.542 430 0.590 0.589 0.5950.590 0.683 0.641 0.691 0.804276.90 276.87/ 843.913 0.295 0.289 0.291 0.276 0.423 0.267 0.312 0.309 0.408 431 276.89 276.64/ 432 845.522 0.498 0.493 0.495 0.453 0.455 0.482 0.508 0.622 0.627 276.68 276.59/ 845.925 0.287 0.292 0.292 0.274 0.296 0.309 0.395 433 0.264 0.358 276.59 276.65/ 434 846.733 0.418 0.412 0.412 0.378 0.386 0.405 0.399 0.452 0.509 276.70

s<1 desc 1<s<1.5 a 1<s<1.5 d 1.5<s<2 a 1.5 <s<2 d s>2 a

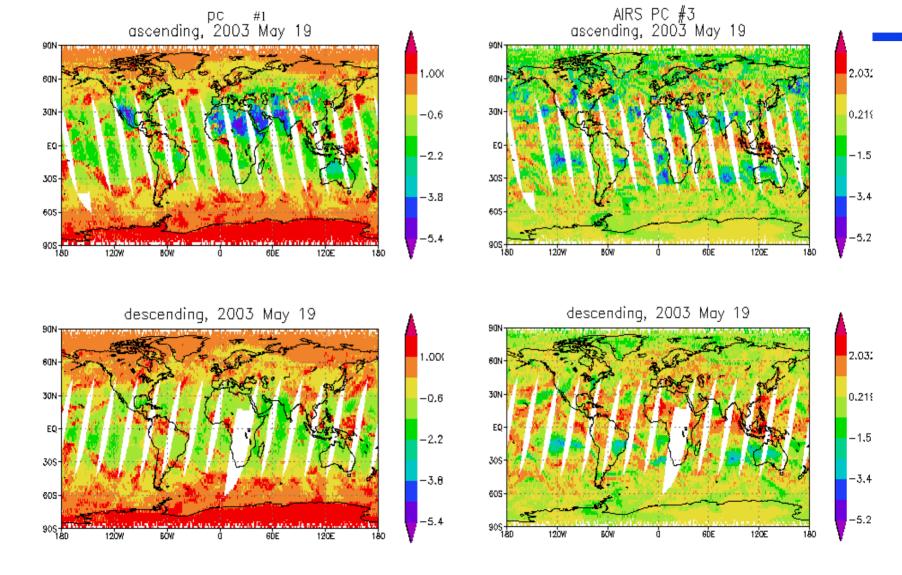
s>2 d



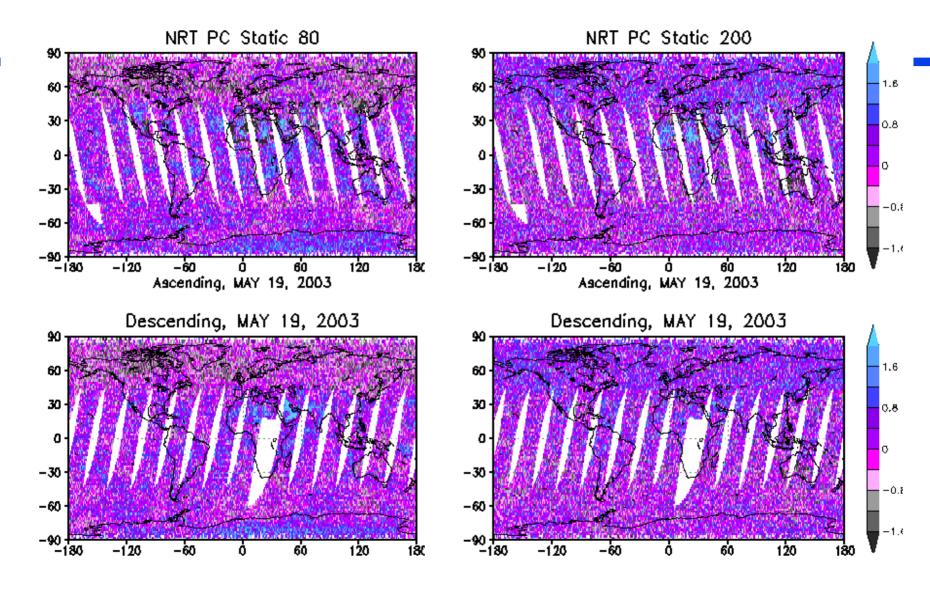
QA Flag: 64- Bad Telemetry 128- High Noise













PC Regression retrievals

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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25	0.027 0.057 0.107 0.181 0.365 0.740 1.331 2.513 5.148 10.707 21.788 38.154 62.214 97.508 154.049 245.160 321.809 367.255 425.302 497.472 576.371 662.038 754.468 853.619 959.407	240. 235 240. 235 240. 235 243. 998 254. 193 262. 260 259. 519 248. 332 234. 652 226. 589 220. 779 215. 030 209. 446 206. 399 212. 950 224. 303 235. 806 242. 400 249. 901 257. 812 264. 907 271. 346 277. 064 281. 082 285. 599	-0.046 -0.046 -0.051 -0.010 -0.033 -0.203 -0.010 0.089 -0.065 -0.186 -0.020 0.044 0.033 -0.071 0.050 0.023 0.002 0.021 -0.068 -0.173 -0.191 0.006	2.873 2.873 2.873 2.322 1.983 2.286 2.112 1.778 1.096 0.941 0.840 0.828 0.791 0.842 0.878 0.878 0.833 0.883 0.883 0.936 0.973 1.060 1.090	1.196 1.196 1.196 0.952 0.780 0.872 0.814 0.716 0.484 0.426 0.391 0.395 0.449 0.372 0.375 0.372 0.344 0.343 0.323 0.345 0.345 0.351 0.377 0.381	2840 2840 2840 2840 2840 2840 2840 2840	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25	0.027 0.057 0.107 0.181 0.365 0.740 1.331 2.513 5.148 10.707 21.788 38.154 62.214 97.508 154.049 245.160 321.809 367.255 425.302 497.472 576.371 662.038 754.468 853.619 959.407	239.971 239.971 239.971 243.822 254.300 262.399 259.369 248.846 235.258 226.898 220.889 214.895 209.019 205.800 212.609 224.253 235.963 242.517 250.029 258.070 265.107 271.455 277.265 281.495 285.987	0.306 0.306 0.306 0.264 0.105 0.016 0.169 -0.043 0.033 0.151 -0.257 -0.063 0.035 -0.114 -0.164 -0.072 0.029 0.141 0.185 0.105 0.037 0.018 -0.064 -0.053 -0.097	3.133 3.133 2.601 2.043 2.072 2.020 1.847 1.724 1.084 0.994 0.748 0.803 0.907 0.884 0.983 0.960 0.918 0.860 0.918 0.894 0.894 1.056 1.056 1.247	1.306 1.306 1.306 1.067 0.803 0.789 0.779 0.742 0.733 0.478 0.450 0.348 0.441 0.416 0.416 0.355 0.367 0.367 0.305 0.348 0.3434	2772 2772 2772 2772 2772 2772 2772 277
26 27 28 29 30 31 32 33 34	122.701 166.353 225.145 301.794 401.665 538.612 709.941 894.219 986.067	0.002 0.000 0.002 0.009 0.034 0.128 0.397 1.293 1.849	0.000 0.000 0.000 0.000 0.000 0.004 0.017 -0.008 0.013	0.000 0.000 0.001 0.003 0.013 0.049 0.141 0.188 0.255	1.284 37.853 36.058 36.657 39.428 37.873 35.387 14.541 13.795	2840 2840 2840 2840 2840 2840 2840 2803 2840	26 27 28 29 30 31 32 33	122.701 166.353 225.145 301.794 401.665 538.612 709.941 894.219 986.067	0.002 0.000 0.002 0.009 0.034 0.147 0.459 1.355 1.998	0.000 0.000 0.000 0.000 0.001 0.002 0.017 -0.004 0.016	0.000 0.000 0.001 0.003 0.014 0.053 0.144 0.206 0.275	1.572 41.958 36.143 38.434 41.828 35.692 31.425 15.206 13.781	2772 2772 2772 2772 2772 2772 2772 277
35 36 37 38 39 40 41 42 43	1.564 3.115 6.121 11.311 21.788 45.055 97.417 184.540 544.011 852.788	6.538 11.039 25.737 36.662 61.484 56.720 29.089 15.227 33.658 276.156	-0.040 -0.072 -0.242 -0.367 -0.363 -0.206 -0.436 -0.079 -0.420 -2.225	0.158 0.245 0.760 1.227 2.062 4.807 4.581 3.271 2.806 8.628	2.420 2.218 2.954 3.346 3.354 8.476 15.747 21.480 8.337 3.124	2840 2840 2840 2840 2840 2840 2840 2840	35 36 37 38 39 40 41 42 43	1.564 3.115 6.121 11.311 21.788 45.055 97.417 184.540 544.011 852.788	6.456 10.953 25.923 37.331 62.395 56.402 29.444 16.019 33.868 278.792	-0.017 -0.081 -0.363 -0.532 -0.773 -0.749 -0.293 -0.130 -0.549 -3.487	0.153 0.269 0.866 1.375 2.489 5.251 4.546 3.427 3.024 10.193	2.362 2.460 3.342 3.683 3.989 9.310 15.440 21.396 8.929 3.656	2772 2772 2772 2772 2772 2772 2772 277



Compression Factors

- 200 pc scores ~ 9.5 % of the total (lossy compression).
- For near lossless compression. Store 80 pc scores plus the residual. The residual can be stored as 1 byte as long as residual is +- 1.28 K. Allows for both noise filtering and lossless compression.
- Not all channels will be within +- 1.28 K, but no more than 20 channels per fov.
- Full data set 2100 x 4 bytes = 9400
- Compression 80 pc x 4 bytes + 2100 ch x 1 byte + 20 outliers x 4 = 2500 ~ 27 %
- Bit trimming can provide even greater lossless data compression (perhaps 10%).



Summary

- All sky eigenvectors
- Monitor reconstruction scores
- Quality control and bad channel handelling
- Provide to NWP centers 200 pc scores (normalized by sqrt(eigenvalues)).
- Also provide subset of individual channels (to monitor the reconstruction).
- Need additional work to study noise filtering feature of eofs.